A Review: Arrhythmia Features Detection Analysis and Deep Learning Method for Wearable Devices

Ratna Lestari Budiani Buana[1], Imroatul Hudati[2]

***Abstract*—Arrhythmia is one of the heart abnormalities which probably not a life threat in a short time but could cause a long-term interference in electricity of the heart. Even so, it should be detected earlier to have proper treatment and suggest a better lifestyle. Arrhythmia diagnosis is usually made by performing a long recording ECG by using Holter monitoring then analyzing the rhythm. Nevertheless, the observation takes time, and using Holter in several days may affect the patient's physiological condition. Previous research has been conducted to build an auto-detection of arrhythmia by using various datasets, different features, and detection methods. However, the biggest challenges faced by the researcher were the computation and the complex features used as the algorithm input. This study aims to review the latest research on the data used, features, and deep learning methods that can solve the time computation problem and be applied in wearable devices. The review method started by searching the related paper, then studied on the data used. The second step was to review the used ECG features and the deep learning method implemented to detect arrhythmia. The review shows that most researchers used the MIT-BIH database, even it requires a lot of effort on the pre-processing. The CNN is the most used deep learning method, but time computation is one of the considerations. The ECG interval features in the time domain are the best feature analysis for rhythm abnormality detection and have a low computation cost. These features will be the input of the deep learning process to reduce computation time, especially on wearable device applications.**

***Keywords*—Arrhythmia Detection, ECG Features, Deep Learning, Wearable Devices, MIT-BIH Database, RR Interval.**

I. INTRODUCTION

The heart is the main organ in the human body. It serves to pump blood to the lungs and throughout the body, making its role very important for the human body's stability. Cardiac abnormalities can come from various problems, such as congenital heart structure abnormalities, due to heredity, or it can also be due to an unhealthy lifestyle, either from food, smoking, or inappropriateness in doing heavy work or sports [1]. Heart disease is grouped into several types based on damage or abnormalities experienced and the cause [2], namely as follows.

1) Coronary Heart Disease: This disease is generally caused by an unhealthy lifestyle. Coronary heart is caused by blockage due to the cholesterol buildup in the blood vessels, especially in the arteries. This blockage will result in impaired heart performance.

2) Congenital Heart Disease: Congenital heart disease is generally experienced from birth. Abnormalities cause this disease in the heart structure, such as imperfect walls or heart valves.

3) Arrhythmia: Arrhythmia is a disease that causes the heart rhythm to be disrupted. Many things cause this abnormality, such as an unhealthy lifestyle, improper exercise habits, genetic disorders, and age.

4) Endocarditis: Endocarditis results from an infection in the heart's inner lining called the endocardium. If not treated immediately, this condition can result in damage to the valves and also stroke.

A. Electrocardiograph (ECG)

All of the above abnormalities can be detected through a heart record or called an electrocardiograph (ECG). An ECG is a device that can record heart activity by placing several electrodes on the thorax area. The resulted recording will describe the occurring heart activity so that it can record existing abnormalities.

ECG signal is a signal produced by the body due to bio-electrode occurring in the body. Electrode-captured ECG signals generally have a voltage of 2 mV [3]. Therefore, adequate signal amplifiers and conditioning are needed to obtain informative results. The weak voltage generated makes the conducted signal processing must be accurate in order to highlight important information but can suppress the noise carried that may have a greater voltage.

Recording from various sides is needed to obtain the signal of heart activities. The heart is depicted as a famous person who will be documented from several sides. A several-side recording is needed to obtain total heart activity as many as twelve leads, namely six leads on the frontal plane (FP) and six leads on the horizontal plane (HP). The FP consists of three bipolar leads, called the Einthoven triangle, which are as follows [4].

1. Lead I, which is the potential difference between the left hand (LA) and right hand (RA).
2. Lead II, which is the potential difference between the right hand (RA) and left foot (LL).
3. Lead III, which is the potential difference between the left hand (LA) and the left leg (LL).

Then the other three leads are monopolar, namely VR (right shoulder), VF (left leg), and VL (left shoulder). These three leads have a positive lead recording the center of the heart and a negative lead measuring from the center of the heart in the opposite direction, as shown in Fig. 1 [5].

[1,2] *Department of Electrical Engineering and Informatics, Vocational School, Universitas Gadjah Mada, Bulaksumur, 55582 Sleman, INDONESIA (phone: 0274-541020; e-mail: [1]ratna.lestari@ugm.ac.id, [2]imroatul.hudati@ugm.ac.id)*

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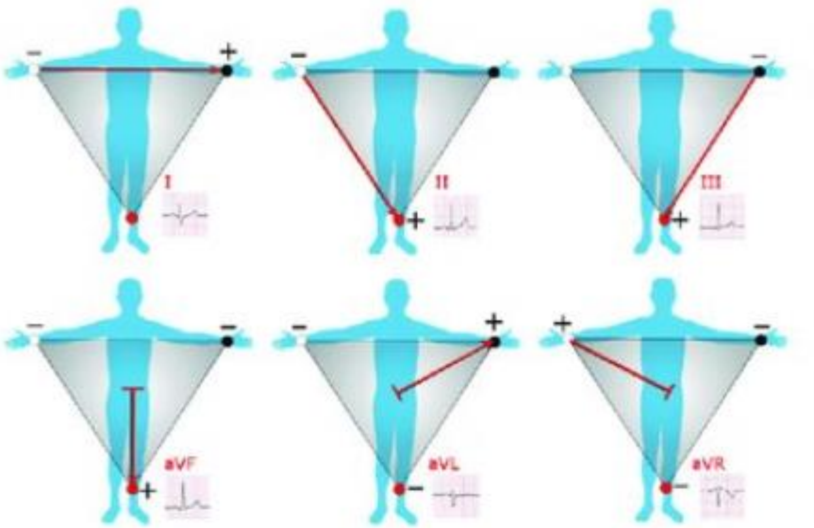

Fig. 1 Frontal plane leads.

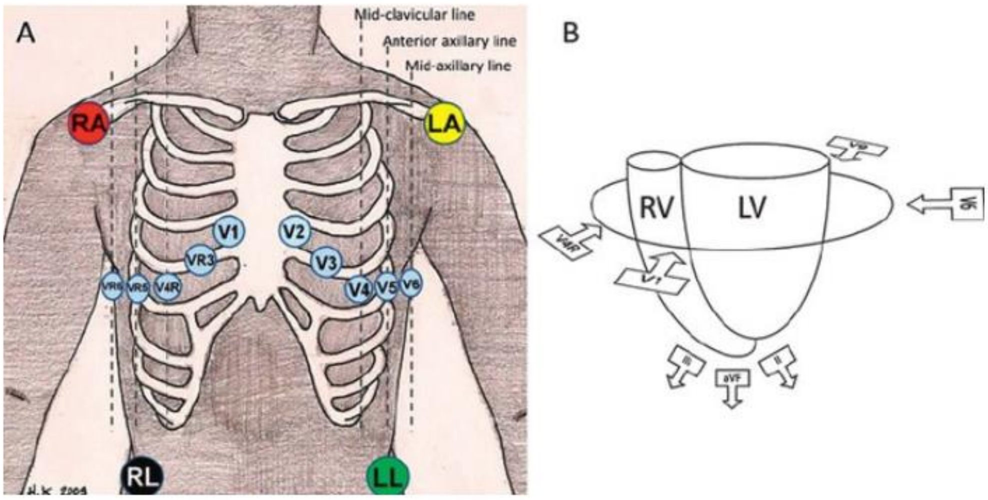

Fig. 2 Precordial leads.

At the same time, there are six leads (precordial leads) on an HP that also record cardiac activities, as shown in Fig. 2 [4]. All of these recordings will later be able to project cardiac activities from the front side so that the ECG can be used to detect abnormalities occurring in the heart [6].

The ECG signal has several parts that can represent the cardiac activity, from the entry of blood into the atria to pumping it out of the heart to the lungs and throughout the body. The ECG signal consists of several parts with five main components whose voltage varies according to the biopotential activity produced by the heart [7].

Fig. 3 and Fig. 4 [8] describe the heart's polarization and depolarization activities to produce an ECG signal consisting of the following things [9].

1) P wave: This wave is generally small in size, which is the depolarization of the atria in response to the sinoatrial node (SA node). The voltage generated by this wave is approximately 0.1 mV. Abnormalities in the atria will cause abnormalities in this wave.

2) PR Interval: This interval is the isoelectric line connecting the P and QRS waves. These waves represent electrical activity from the atria to the ventricles, i.e., filling the ventricles with blood. Impaired conduction from the atria to the ventricles will cause changes in the PR segment.

3) QRS Waves: The QRS complex waves are a group of waves resulting from right and left ventricular depolarization. These waves generate a biopotential of up to a maximum of 2.0 mV.

4) ST Interval: This segment is an isoelectric line connecting the QRS complex and the T wave.

5) T Wave: The T wave represents the repolarization potential of the right and left ventricles. The generated voltage is slightly larger than the P wave, which is up to 0.2 mV.

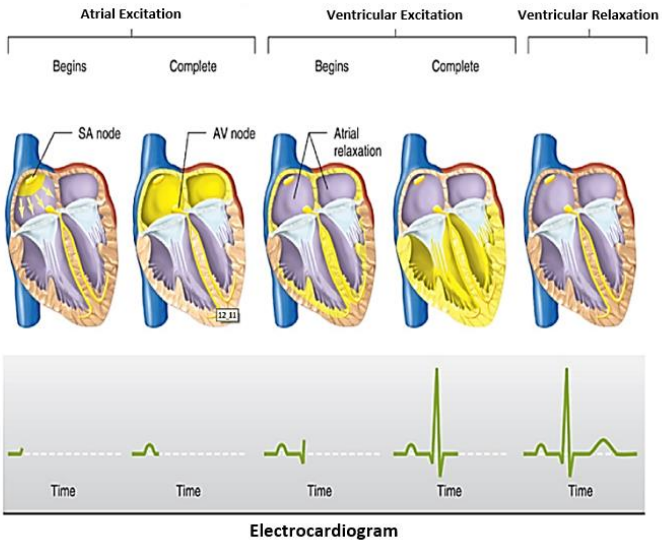

Fig. 3 Cardiac activity and ECG signals.

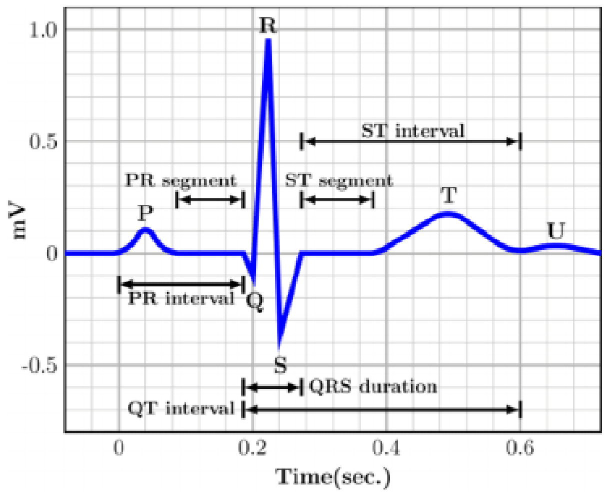

Fig. 4 ECG signal.

B. *Arrhythmia*

Arrhythmia is a disorder occurring in the heart rhythm. Arrhythmia patients will experience an abnormal heart rhythm; it can be faster, slower, or changing. Arrhythmia conditions are common even in healthy hearts. However, if it occurs continuously or repeatedly, an arrhythmia can indicate a problem with the heart organ. Arrhythmias can occur without symptoms so that the patient is unaware of them, but can also have symptoms such as dizziness, fatigue, or chest pain [10].

The normal heart rate (HR) for adult ranges from 60 to 100 beats per minute, depending on the activity performed. In athletes who routinely perform physical activity exercises, the normal heart rate ranges from 40 to 60 beats per minute [11]. Under normal conditions, the heart will automatically beat faster when doing strenuous activities, such as exercising, because it requires more oxygen. Then, at rest, the number of beats per minute will decrease. In people who have a heart rhythm disorder, the rhythm condition will not be related to the performed activities. These changes are associated with changes in tissue and electrical activity in the heart [12].

Arrhythmias are also common in athletes who are generally young and male [13]. Athletes' activities, which are generally strenuous activities, result in stronger heart walls than people who do not exercise enough [14]. The fluctuating activity of athletes with a large activity load triggers an unstable heart rhythm.

Judging from the signal, arrhythmias can be seen from HR abnormalities (per minute) in a reasonably long recording duration. If viewed from the theory of the occurrence of arrhythmias and also the number of beats that is more or less than normal, the QRS wave or the crest of the R wave will look denser or more distant due to an abnormal rhythm, which will result in the RR interval, i.e., the distance of the R to R wave, will be high in variation compared to the RR interval of healthy people [15]. There are several often-found types of arrhythmias, which will have an impact on the ECG signal.

1) Atrial Fibrillation (A-Fib): Atrial fibrillation (A-Fib) is a condition when the heart beats faster and irregularly, which can lead to blood clots, heart failure, and other complications. Under normal conditions, the heart will contract and relax with a normal rhythm, but in A-fib conditions, the atria do not work properly to continue to the ventricles [16]. As a result, there is a vibration signal captured by the ECG. This condition will cause incomplete blood pumping. Judging from the ECG signal, A-fib patients generally have very low or even imperceptible P wave amplitudes, as shown in Fig. 5 [17].

2) Atrioventricular Block (AV Block): Atrioventricular block (AV block) or heart block is a condition when there is a delay or interruption in signal transmission when the heart distributes blood from the atria to the ventricles. As a result, the beat becomes slow or missed [18]. There are several types of AV blocks, depending on the severity and symptoms experienced. If the occurring block is rare, it can be classified as mild. However, frequent and long-duration blocks will result in heart failure [19] because the abnormal electrical output will result in the ECG signal, as shown in Fig. 6 [20]. At some time, the signal is lost and is not recorded by the EKG.

3) Supraventricular Tachycardia: Supraventricular Tachycardia, also known as paroxysmal, is a condition when the heart beats too fast, which is above 100 beats per minute. Heart rhythm is regulated by the sinus node in the right atrium. The nodes will issue an electrical impulse with each heartbeat. The heart beats so fast that it causes the heart muscle to relax between contractions [16]. When this condition occurs, the walls of the ventricles cannot contract perfectly, thus interfering with the need for blood throughout the body, especially the brain. The result of this disorder is that the ECG signal of patients with tachycardia is different from the ECG of normal people; that is, there is almost no P signal and an uneven (flat) ST interval, as shown in Fig. 7 [17].

4) Bradycardia: Bradycardia is the opposite condition of tachycardia, which is a slow HR. Bradycardia is often found in both healthy and sick people. And this type of arrhythmia results from temporary dysfunction. Bradycardia is asymptomatic and is not a threatening disorder [21]. However,

Fig. 5 ECG signals for atrial fibrillation.

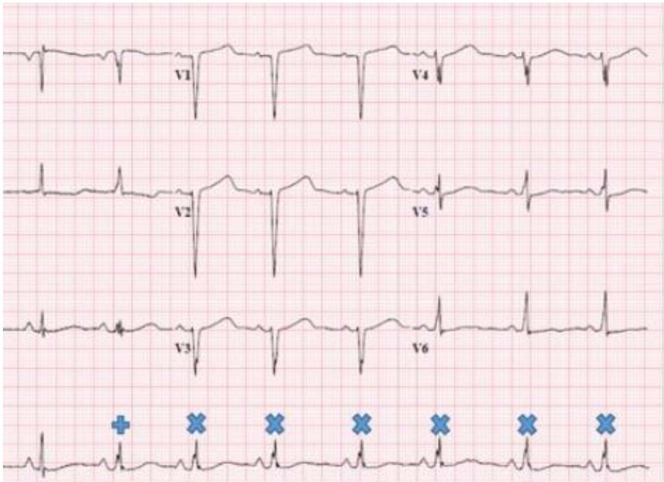

Fig. 6 ECG signals for AV block.

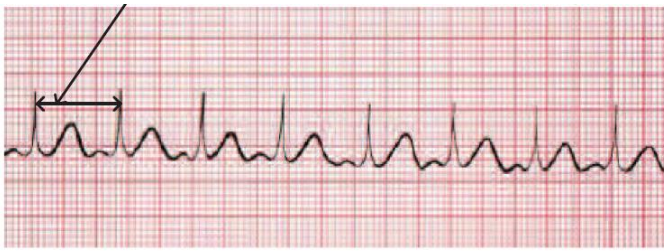

Fig. 7 ECG signals for supraventricular tachycardia.

Fig. 8 ECG signals for bradycardia.

the discovery of bradycardia allows other organ disorders besides the heart, such as sleep apnea. This disorder will be seen in the recorded ECG signal, as shown in Fig. 8 [17].

C. Detection Challenges

Several studies have been conducted to examine how to detect arrhythmias. Although the abnormality of arrhythmias is rhythm-related, so that interval is the key to detection, many other components of the ECG signal can serve as features for arrhythmia detection [22]. Moreover, the symptoms or features characterizing arrhythmias are not always apparent during recording [16]. Therefore, continuous recording using a device such as a Holter monitor is required, which is not always available in every hospital.

A person's heart signal condition is also greatly affected by many factors from the subject, such as age, gender, physical condition, and lifestyle. Therefore, when data is used in a study with a research object under certain conditions and then tested with a different research object, the obtained results are not as good as when an object with the same characteristics is used. Hence, it can be concluded that the detection accuracy is still lacking when its primary function is to determine the diagnosis. In addition to the object's features, other things that have an effect are the environment or condition of the object when it is recorded, active, or resting.

The complexity of the detected features will affect the computation time, thus impacting the real-time detection. Another challenge is the data with a lot of noise so that adequate preprocessing is needed; therefore, the obtained data is relatively informative [23] when recording is done directly, noise from the electrodes is very likely to occur, i.e., from movement, breathing, or noise from the power source. In addition, the secondary datasets available and used to detect arrhythmias have an extensive variety of classes, making detection more difficult.

Several academic works of literatures related to arrhythmia reviews have also been carried out. One of them is examining the accuracy of mobile devices to detect A-Fib [24]. The review is done by looking at the utilized hardware technology, its characteristics, and also its accuracy. The performed review illustrates that the detection of arrhythmias on mobile devices has begun to be considered, especially for its accuracy. Other reviews have been carried out on studies applying deep learning to classify several types of arrhythmias [25]. Several arrhythmias that conducted studies have detected have their own characteristics as well as weaknesses and advantages. Another review focused on using the Massachusetts Institute of Technology - Boston's Beth Israel Hospital (MIT-BIH) database from PhysioNet to detect arrhythmias [23]. This review focuses on the process performed on the MIT-BIH dataset in detecting arrhythmias. The MIT-BIH database is compelling data and is widely used in many studies. However, in addition to these advantages, a lot of data cannot be optimally used due to its long age. Therefore, it affects the detection results if the pre-processing is not appropriately performed.

Based on the data mentioned in the introduction, the purpose of this study is to review the studies carried out to detect arrhythmias, starting from the data used, the features detected, and the employed deep learning methods leading to the algorithm application on wearable devices.

II. METHODOLOGY

This study commenced by examining the data used in previous studies. The literature search was carried out using the keywords of arrhythmia, detection, and deep learning, which would lead to several technical and health journals. The

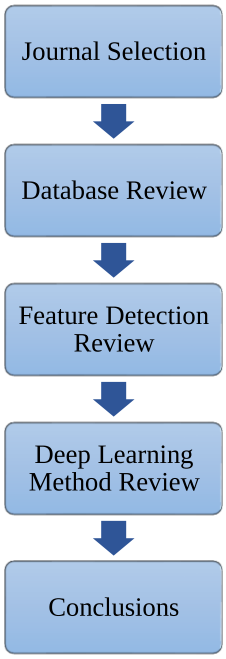

Fig. 9 Review method.

literature taken was those published in the last five years. However, it was possible that there was some literature that was more than five years old to find out which databases were used or the features that were processed. The literature was separated using a table related to the components used within. The first component to be studied was the database used by the research, i.e., primary or secondary data. Furthermore, the ECG features used were analyzed to determine the complexity of the features when processed so that they affected the next computation. The last section was a review of the right deep learning methods applied to wearable devices. This review was carried out in several stages, as shown in Fig. 9.

A. Database

Research that had been carried out to detect arrhythmias was to conduct studies using ECG data from patients with arrhythmias by comparison with heart data without arrhythmias. Some studies utilized data directly taken from patients in certain hospitals [26]. However, most of the research that had been done utilized secondary data from PhysioNet [27].

PhysioNet is a database developed by the National Center for Research Resources of the National Institutes of Health. The source of this database is from two parts that can support innovation. The first part is PhysioBank, an online media forum for researchers to exchange data to support research and propose new algorithms. Meanwhile, PhysioToolkit is a library containing signal processing and open-source analysis techniques. Both sections are placed free of charge in a free web application that can support various skill levels and fields of knowledge [28].

PhysioNet provides data called MIT-BIH, which is data sourced from Boston’s Beth Israel Hospital (BIH), which has now changed its name to Beth Israel Deaconess Medical Center

TABLE I
THE NUMBER OF FEATURES USED IN PREVIOUS RESEARCH

Feature	Total
RR interval	8
P wave	2
R wave	2
T wave	1
All ECG components	15

in collaboration with the Massachusetts Institute of Technology (MIT) since 1975 to conduct research associated with arrhythmias. The MIT-BIH Arrhythmia database is a 48-hour recording of heart activity from 47 subjects. The subjects consisted of 25 men between the ages of 32 and 89 and 22 women from 23 to 89. As many as 60% of the subjects were not patients in BIH. The recording was done with two channels, the first was lead II in FP, and the second was V1 on precordial leads [27].

In addition to the MIT-BIH Arrhythmia database, some databases from MIT-BIH associated with arrhythmias that can also be used are

- Long Term Atrial Fibrillation Database,
- MIT-BIH Arrhythmia Database P-wave Annotation,
- MIT-BIH Arrhythmia Atrial Fibrillation Database, dan
- MIT-BIH Noise Stress Test Database.

Comparison data, i.e., data without arrhythmias, was obtained from the MIT-BIH Long Term ECG Database and MIT-BIH Normal Sinus Rhythm Database (NSRD).

Besides using secondary data that has been available, some studies also use data taken directly from patients, such as data taken in Shaoxing, Zhejiang University Hospital [26], and also data from Creighton University Ventricular Tachyarrhythmia (CUDB) [29]. For research with specific arrhythmia objectives and with research cooperation with the medical field, primary data will be better used to avoid getting biased and so that detection is more precise and accurate.

B. Detection Features

Several features of the EKG record are utilized to detect arrhythmias. Generally, arrhythmias can be detected using irregular HR, so the interval of the ECG signal is a widely used feature [30]. The entire interval of an ECG wave has potential in arrhythmia detection. More specifically, some studies only use RR intervals by ignoring other intervals [31]. Research using R waves as a detection feature will reduce costs and be suitable to be applied for mobile ECGs and real-time detection [32].

However, some studies have also used other features, such as P waves, which are depolarization signals from the atria. Moreover, tachycardia or high-rhythm arrhythmias generally make P waves invisible because the RR intervals are too tight. However, detection of P waves is also not easy because P waves have a minimal voltage, do not have time and frequency characteristics, and have high variation between patients [33].

Not only P waves, but T waves are also one of the features researchers chose to detect arrhythmias [34]. This study employed T waves hybrid features. Wave P represents the depolarization of the atria, while T wave is the repolarization

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of the ventricles [35]. Both of these waves are in an adjoining position, so T waves are also potential waves to detect arrhythmias.

Other studies used an ECG signal form of arrhythmia. The form feature of some ECG signals with multiple arrhythmias is used as deep learning input [36]. However, there are challenges in the detection method using the form feature, i.e., frequent errors in detecting ECGs under normal conditions and also A-fib. Of the 28 literatures, the number of studies with a variety of specific methods and features is shown in Table I.

C. Arrhythmia Detection Methods

The complexity of features to detect arrhythmias led the researchers to apply deep learning as a detection method. Before applying deep learning, pre-processing was conducted to make training more optimal. The implemented deep learning has a variety of purposes, such as detecting arrhythmias or detecting certain types of arrhythmias [37]. The study utilized artificial neural networks (ANN) with multi-layer perceptron (MLP). The algorithm has successfully classified ten types of arrhythmias from 92 patients. The study also performed several segmentation variations and showed that fuzzy c-means clustering (FCM) could help reduce the same segments on training data. Other studies classified arrhythmias using hybrid support vector machine (SVM) algorithms and were assessed to reduce detection errors [38].

In addition to using ANN, other studies utilized machine learning in detecting arrhythmias using random forest (RF) classifiers by decomposing ECG signals using discrete wavelet transform (DWT) into multiple frequency bands. The obtained accuracy was relatively good, but the computing time was still high. Other studies used frequency domains, i.e., by extracting ECG signals with Fourier transforms and represented through a spectrogram [35]. The first approach was to use SVM and the second was to use convolutional neural networks (CNN). Results from the CNN method showed an accuracy of 93.16%, with the weakness of being unable to precisely detect A-Fib [39].

The most widely found method for detecting arrhythmias is CNN, which is claimed to reduce a lot of computing time. One of them is research that aims to classify heart rate disorders. Using nine layers of CNN, with original data and data, accuracy was obtained at 94.03% and 93.47% [40]. Next, the same researchers developed the method by detecting multiple ECG segments to detect A-Fib, atrial flutter, and ventricular fibrillation using eleven LAYERS of CNN. The resulting accuracy was 92.05% for a five-second EKG recording [41]. Other CNN methods were also applied to detect ventricular arrhythmia and ventricular tachycardia. The data used in this detection was a two-second EKG recording with eleven CNN layers [42].

CNN and MLP were also applied to the study to classify certain types of arrhythmias. However, in detection, AV block and ventricular were considered to interfere with the network that had been built so that miss detection occurred. The obtained accuracy was 83.5% for CNN and 88.7% for MLP [36]. Another deep learning approach was conducted in a study using data from MIT-BIH Arrhythmia and tested with several classifier algorithms. The application of deep learning is considered very efficient and has a reliable accuracy rate [31].

Another deep learning study was to detect A-Fib using CNN and recurrent neural networks (RNN). The feature used was the RR interval. The algorithm was built using a database of 89 patients and then tested with real-time data. The results showed an accuracy of 98.96% specificity and 86.04% sensitivity. These results can be a pioneer that the resulting algorithms can be applied with real-time data, but with more significant data to test their accuracy [43]. Deep CNN (DNN) was also used to detect arrhythmias using the Bat-Rider optimization algorithm (BaROA). The Gabor feature was first extracted from the EKG

TABLE II
THE DEEP LEARNING METHOD AND ACCURACY RESULTS

Year	Research	Deep Learning Methods	Advantages	Weakness
2020	[30]	Deep CNN with BaROA optimization	Good accuracy with 93.19% and 95% of sensitivity and specificity respectively.	Not capable enough to handle dynamic features.
2020	[26]	Deep CNN and Max Pooling from 12-lead ECG data	Good accuracy for every lead on each type of arrhythmia.	Data used was 10 seconds ECG recording.
2019	[39]	SVM and CNN	Good accuracy, 92.18% for SVM and 93.16% for CNN.	CNN input is the spectrogram construction from 6 seconds ECG recording with A-Fib.
2019	[43]	CNN and RNN	Good accuracy of 98.96% with real time data.	Only 89 patients with A-Fib used to build the model.
2018	[44]	Deep CNN with Continuous Wavelet Transform (CWT)	Good accuracy with three databases: MIT-BIH, INCART and SVDB.	CWT should be modified to transform ECG.
2018	[36]	CNN and MLP	The accuracy classification is satisfying.	Av block and ventricular data troubled the network.
2018	[42]	CNN	Capable to detect ventricular arrhythmia and ventricular tachycardia in shockable moment.	Focus on shockable moment, the data use is only two seconds.
2016	[35]	Random Forest Classifier and DWT	Good accuracy above 99%.	Heavy computation.

signal, and then the DNN was applied. Using data from MIT-BIH Arrhythmia, the obtained accuracy was 93.19% [30].

Table II shows several different types of method combinations from recent research using deep learning and its weaknesses and disadvantages. For the application of wearable devices, the things that need to be underlined are lightweight computing, real-time data usage, and satisfactory accuracy.

D. Real-Time Detection on Wearable Devices

Several studies have been conducted to examine the possibility of algorithms being applied to real-time data. One example is by using multi-section vector quantization (MSVQ) to decrease the computing time. However, the study did not pay attention to accuracy but only focused on large datasets. The utilized data was MIT-BIH recording data, not by testing using dynamic data [45].

A study was conducted on Kardia Band (KB) technology that has been introduced by the Food and Drug Administration (FDA) for Apple companies that were able to record patient data almost the same as lead I FP for 30 seconds through a single strip [46]. The KB was claimed to be able to detect one type of arrhythmia, i.e., A-Fib. The study was conducted on 100 patients. The obtained result was that KB had 93% sensitivity and 84% specificity compared to EKG results. KB was considered capable of separating between A-Fib and sinus rhythm (SR) [46]. A review examining m-health innovations in A-Fib detection stated that detection innovations had not been able to exceed the expected accuracy, but this detection was useful for detecting A-Fib in the paroxysmal form [47].

Another study proposed a mild R wave real-time detection method for ECG exercise signals [32]. Max-min threshold (MMT) was used to detect R waves in real-time resulting in box waves. The results showed a sensitivity of 99.7% with light computing with a little noise. However, the test was conducted with MIT-BIH data, not real data that allowed other weaknesses to be discovered [32].

The application of wearable devices indeed cannot be separated from the internet of things (IoT) design, both in terms of software and hardware. Research comparing light deep learning and machine learning on detection using IoT devices shows that deep learning is lighter and performs well on multiple hardware devices. However, tastings were conducted using data from MIT-BIH [48].

In the future, wearable technology will continue developing and producing better detection. In its development, of course, there will be various challenges and shortcomings. However, wearable technology is considered to be very helpful, both for medical needs and for improving the quality of life, especially to detect heart failure [49].

III. DISCUSSION

From the utilized data, most of the research was conducted using data from PhysioNet, which was relatively robust with a label and gold standard that could be used as a reference. In addition, the PhysioNet data consisted of normal ECG data as well as various types of arrhythmias. However, in pre-processing, the segmentation process to extract the features required a reasonably heavy effort. In addition, a study stated that the data from PhysioNet was unbalanced. The data provided was relatively large, but after the pre-processing stage, only a small part of the data was effective [23]. Therefore, several types of data were used and combined in the conducted research.

In medical examination conditions, arrhythmic patients were asked to record their heart activity for a long time using an ECG or Holter, which was an ECG recorder that could be carried for 24 to 72 hours. This detection would be very helpful in summarizing extensive data allowing a diagnosis to be made. In addition, the arrhythmia detection method was also very appropriate if applied for early detection. Arrhythmia is not a heart disorder that can be fatal in a short time. However, if not given immediate action, arrhythmias can result in abnormalities in the heart and other organs. Therefore, rapid detection will be very useful, although, in the end, the diagnosis is left to experts. So, the features that are potentially used are features requiring low computation.

Based on the features used in the detection, several studies utilized intervals, intervals, and amplitudes, as well as features extracted in other domains. The more features used, of course, the better. Nevertheless, the computation would be more prominent, especially if the retrieved data were in the time domain, while the detection algorithm was carried out in a different domain. In addition to high computation time, conversion to the frequency domain will also result in errors; Moreover, the ECG signal, especially for people with arrhythmias, has an unstable frequency.

Referring to the research that has been done, it can be concluded that the deep learning method is relatively robust in detecting arrhythmias because of the relatively complex features involved in the training process. Deep learning is applied to data in the time domain and in the frequency domain and in the form of extracted images.

Deep learning methods were also applied to several processes, such as feature extraction, classification, or both. The most widely used method is CNN. A study applied 10,000 data from twelve lead ECG patients at Shaoxing Hospital [26]. CNN is used in the learning phase and generates the highest accuracy, which is up to 96.13%. In addition, CNN is also considered to be used for real-time detection as well as research related to IoT in detecting arrhythmias using smartwatches [48]. From this research, it can be concluded that computing becomes much lighter and can also be applied to real-time data by using CNN.

The data used for research on wearable devices in detecting arrhythmias was also secondary data from MIT-BIH, not from patient data. In applying algorithms with certain work tools, new problems will certainly be found.

IV. CONCLUSIONS

This study provides conclusions for several methods that have been implemented along with the data and detected features. This review aims to examine the data use, detected features, and deep learning methods to detect arrhythmias.

The widely used data in previous studies originate from PhysioNet, both normal ECG data, and ECG data with abnormalities, both arrhythmias and other abnormalities. However, PhysioNet data is complex raw data that requires pre-processing. The features used in the research are also diverse. However, the frequently faced challenge is the feature complexity, resulting in a significant increase in computation time. For applications on wearable devices that will get real-time data input and with limited hardware specifications, the lightest and most potential feature for arrhythmia detection is the RR interval with analysis in the time domain. Like the applied deep learning method, CNN is a potential method for detecting arrhythmias on wearable devices because of its light and rapid computing.

There are still many challenges faced in detection with wearable devices. One of the formidable challenges is how to reduce the complexity of medical instrumentation in small packages while maintaining its accuracy, also with variations in user usage. However, early detection by utilizing wearable technology will be beneficial in the future and is very likely to be realized, both for medical purposes and personal monitoring.

CONFLICTS OF INTERESTS

The author declares that no conflict of interests, either in certain circumstances or personal interests, will affect the representation or interpretation of the research results.

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